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Using simulation to map fire regimes: an evaluation of approaches, strategies, and limitations*

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Abstract. Spatial depictions of fire regimes are indispensable to fire management because they portray important characteristics of wildland fire, such as severity, intensity, and pattern, across a landscape that serves as important reference for future treatment activities. However, spatially explicit fire regime maps are difficult and costly to create requiring extensive expertise in fire history sampling, multivariate statistics, remotely sensed image classification, fire behaviour and effects, fuel dynamics, landscape ecology, simulation modelling, and geographical information systems (GIS). This paper first compares three common strategies for predicting fire regimes (classification, empirical, and simulation) using a 51 000 ha landscape in the Selway-Bitterroot Wilderness Area of Montana, USA. Simulation modelling is identified as the best overall strategy with respect to developing temporally deep spatial fire patterns, but it has limitations. To illustrate these problems, we performed three simulation experiments using the LANDSUM spatial model to determine the relative importance of (1) simulation time span; (2) fire frequency parameters; and (3) fire size parameters on the simulation of landscape fire return interval. The model used to simulate fire regimes is also very important, so we compared two spatially explicit landscape fire succession models (LANDSUM and FIRESCAPE) to demonstrate differences between model predictions and limitations of each on a neutral landscape. FIRESCAPE was developed for simulating fire regimes in eucalypt forests of south-eastern Australia. Finally, challenges for future simulation and fire regime research are presented including field data, scale, fire regime variability, map obsolescence, and classification resolution.

Additional keywords: mapping; GIS; LANDSUM; FIRESCAPE; simulation modelling; landscape modelling.

Introduction

Successful wildland fire management is partly dependent on accurate and consistent predictions of fire regimes at multiple spatial and temporal scales (Hardy *et al*. 2001). Fire regime maps can portray historical burning characteristics, such as severity, frequency, and pattern, of natural and human-caused fire (Morgan *et al*. 2001). Using fire regime maps, landscape fire treatments can be prioritized, designed, and scheduled from fire frequency and severity descriptions (Heinselman 1985; Barrett and Arno 1992; Agee 1995; Brown 1995). Fire regime maps can also be used to quantify input parameters for landscape models that simulate effects of alternative fire management strategies on landscape dynamics (Keane *et al*. 2002*b*). Fire regime maps also provide a context for interpreting and understanding landscape and fire ecological interactions (Barrett and Arno 1992; Turner *et al*. 1997). And last, fire regime maps can be used to stratify fire monitoring and landscape inventory sampling (Lutes *et al*., in press) (see also www.firelab.org/firemon).

Development of fire regime maps is a difficult and costly task, requiring extensive expertise in fire ecology, fire history sampling, and statistical analysis (Morgan *et al*. 2001). Moreover, since fire regimes are the expression of the interactions between climate, fire, vegetation, and topography, mapping them would require extensive knowledge of fire dynamics, fuels, landscape ecology, simulation modelling,

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remote sensing, and Geographic Information Systems (GIS) (Keane *et al*. 2003). This wide variety of skills is especially important because there are several approaches, strategies and techniques that are usually fused to create accurate and realistic fire regime maps. The key to successful fire regime prediction is to recognize the strengths and limitations of all methods, data, and models and then merge the best parts into a comprehensive prediction vehicle.

In this paper, we focus on the comparatively new method of using simulation modelling for developing fire regime maps. In doing so we will first compare three common strategies for predicting and mapping fire regimes: (1) classification; (2) statistical modelling; and (3) simulation modelling to explore the performance of simulation modelling against these other more traditional methods. Second, we present the advantages, disadvantages, and limitations of simulation modelling to spatially describe fire regimes using three simulation experiments where we vary the simulation time span, fire frequency parameters, and fire size parameters. Then, we will demonstrate how differences in design between two simulation models can affect fire regime predictions by comparing predicted fire regimes generated from the FIRESCAPE (Cary and Banks 1999; McCarthy and Cary 2002) and LANDSUM (Keane *et al*. 1997*b*, 2002*b*) landscape simulation models on a neutral landscape. Future research, including compilation of comprehensive field databases, scale issues, inherent variability, and improved fire regime classifications, are discussed last.

Background

Fire regimes are general descriptions of wildland fire characteristics across discrete time and space bounds. Common fire characteristics used to define fire regimes include frequency, size, pattern, intensity, severity, type of fuel burned, and season of burn (Gill 1975, 1998; Heinselman 1981; Agee 1993). Fire frequency is best defined at the scale of application. Point measures, such as fire return interval and fire probability, describe the number of fire events experienced over time at one point on the landscape. Landscape measures of fire rotation and fire cycle estimate the number of years it takes to burn an area the size of the relevant landscape (Agee 1995; Lertzman *et al*. 1998). The distribution of burn sizes on a landscape or region depends primarily on the number of large fire events; typically only a few fires burn the majority of the area (Yarie 1981; Strauss *et al*. 1989; Bessie and Johnson 1995). Vegetation, topography, antecedent weather, and fuels will often dictate the mosaic of burned patches within and across fires on the landscape (Skinner and Chang 1996; Kushla and Ripple 1997). Fire intensity describes the physical heat output from a fire, whereas fire severity describes the subsequent fire-caused damage to the biota and soils (DeBano *et al*. 1998).

In this paper, we use only frequency and severity to describe fire regimes because they are most important to fire effects and they are used in the majority of studies. The point-based average fire return interval (years) is used to describe frequency. Fire severity is described by three categories commonly adopted for northern hemisphere coniferous forests. Non-lethal surface fires burn surface fuels at low intensities but do not kill many overstory trees. Stand-replacement burns kill that majority of the dominant vegetation, often trees and shrubs (greater than 90% mortality) (Brown 1995). These fires include both lethal surface fires and active crown fires (Agee 1993; Brown 1995). Mixed severity burns contain elements of both non-lethal surface and stand-replacement fires mixed in time and space and include passive crown fires, patchy stand-replacement burns, and mixed severity underburns (Brown 1973, 1995; Shinneman and Baker 1997; Arno *et al*. 2000). Other types of severity classes exist, such as ground fires (i.e. smouldering fire burning extensive duff layers), but for brevity they are not presented here.

It is the cumulative interaction of fire, vegetation, climate, topography, and humans over time that ultimately creates a fire regime (Crutzen and Goldammer 1993). These interactions are spatially and temporally correlated; future burns are influenced in space by the adjacency to burnable stands and fire-resistant topographic features (e.g. lake shores, rock outcrops) and in time by the occurrence and severity of past climate (e.g. El Niño, drought) and disturbance events (e.g. previous burns, insect epidemics). A change in any of these factors will ultimately cause a change in the fire regime and, since all four factors are constantly changing across many scales, fire regimes are inherently dynamic. For example, climate change can affect fire regimes by modifying the weather (Flannigan and Wagner 1991; Cary and Banks 1999), altering fire ignition patterns (i.e. lightning) (Price and Rind 1994; Stocks *et al*. 1998), and increasing fuels and smoke (Keane *et al*. 1997*a*, 1999). Exotic plants, such as cheatgrass and spotted knapweed, have modified fire regimes as they invaded into many arid ecosystems (Whisenant 1990). Humans have influenced past and present fire regimes throughout the world (Barrett and Arno 1982; Pyne 1982; Russell 1983). Native Americans started many burns for a wide variety of reasons including land clearing, wildlife habitat improvement, cultivation, defence, communication, and hunting (Gruell 1985; Lewis 1985; Bahre 1991; Kay 1995). In parts of Australia, Aboriginal burning was common for at least 60 000 years (see Bradstock *et al*. 2002). Because of this dynamic nature of fire, fire regimes should not be viewed as attributes or characteristics of ecosystems or vegetation types. Fires are landscape-level disturbances that do not follow discrete mapping units and are influenced by many factors besides fuels and vegetation (Agee 1993). Attempts to predict fire regimes solely from fuels (Olsen 1981), vegetation (Frost 1998), or topography (Barrett and Arno 1992) have only partially succeeded because these studies have not recognized the pervasiveness of fire on the landscape and the interactions of all factors that control fire dynamics across multiple scales.

Many techniques and methods have been used to predict fire regimes for both stands and landscapes (Morgan *et al.* 2001; Keane *et al.* 2003). We have identified three broad strategies for mapping fire regimes: (1) Classification; (2) Statistical Modelling, and (3) Simulation Modelling. The classification strategy involves assigning a fire regime category to one or more categories in related classification schemes often based on vegetation, biophysical settings, or climate. The popular statistical analysis strategy can use the entire suite of multivariate statistical techniques, such as regression, ordination, general additive models, and logistic regression, to create deterministic or stochastic fire regime predictive models. Last, the simulation strategy uses stand or landscape models to simulate fire events and vegetation development (i.e. succession) over time to generate some spatial expression of fire regime. This strategy is somewhat new because recent advancements in computer technology have allowed an independent spatial simulation of fire spread coupled with weather and topography (Finney 1998).

Each of these strategies can be implemented using three approaches: (1) Stochastic; (2) Empirical; and (3) Physical (see Gardner *et al.* 1999; Turner *et al.* 2001 for review). The stochastic approach uses probabilities and stochastic functions to quantify or describe fire regime. An empirical approach uses field data to derive deterministic relationships to represent characteristics of a fire regime. Examples include regression models, discriminant functions, and other multivariate statistical modelling. The classification strategy may use empirical approaches such as regression trees and neural networks. The physical approach uses formulations of the physical processes driving ecosystems and landscapes to create fire regime descriptions. These approaches are not mutually exclusive and, in fact, the best fire regime predictive models are often created from a melding of approaches.

Since this paper emphasizes simulation modelling, it is important to understand the design and components of the landscape fire succession models that can spatially predict fire regimes. There are usually at least four elements in a landscape fire succession model: vegetation succession, fire ignition, fire spread, and fire effects (see McCarthy and Cary 2002; Keane and Finney 2003 for review). Succession is simulated using a variety of approaches such as a stochastic Markov transition model (Acevedo *et al.* 1995); a species-based vital attributes scheme (Roberts and Betz 1999); an empirical frame-based multiple pathway model (Chew 1997; Keane *et al.* 1999, 2002*b*); a deterministic age-since-disturbance function (Baker 1994; Li *et al.* 1997); a fuel accumulation function (Cary and Banks 1999); an individual plant gap model design (Miller and Urban 1999); or a physical biogeochemical model (Keane *et al.* 1996*b*). Fire ignition is usually modelled with stochastic functions based on Weibull probability distributions (He and Mladenoff 1999; Keane *et al.* 1996*b*) that can be linked to indices of fire weather (Gardner *et al.* 1996; Li *et al.* 2000). Fire spread is often simulated using cell automata, percolation, or vector propagation based on simple topographic rules to physically based fire behaviour models (see Gardner *et al.* 1999; Turner *et al.* 2001 for summaries). The effects of fires are often modelled using a rule-based approach, probabilistic functions, or explicit simulations of fire damage (see Keane and Finney 2003 for summary).

Methods

Mapping strategy comparison

Fire regime maps of fire frequency and severity were created using the three broad mapping strategies presented in the previous section: classification, statistical analysis, and simulation modelling (Keane *et al.* 2003). A portion of the Lower Selway watershed (51 761 ha), located on the western edge of the Selway-Bitterroot Wilderness in the mountains of central Idaho, was used as the analysis landscape. Field data used in this comparison were taken from 64 plots located within this landscape and collected by Keane *et al.* (2002*a*) in 1995 for an intensive ecological inventory of the area. Fire frequency is described by three categories of fire return intervals (0–40 years, 40–100 years, and 100+ years), and fire severity is defined by three general fire type categories: non-lethal surface fire, mixed-severity fire, and stand-replacement fire.

Maps created using the classification strategy employed an empirical approach where the rule-based terrain model of Barrett and Arno (1992) for the greater Selway-Bitterroot Wilderness Area was coded into a GIS to create the frequency and severity maps. Discriminant analysis was used for the statistical analysis strategy to create fire regime maps with an empirical approach. The extensive ecological gradient-based field dataset (Keane *et al.* 2002*a*) used in this analysis contained over 200 variables to predict fire regime including topography, weather, ecosystem processes (i.e. evapotranspiration, net primary productivity simulated from the Biome-BGC models; Thornton 1998), satellite imagery, and soils information. Only discriminant analysis was employed in this statistical approach because Keane *et al.* (2002*a*) found that other more complex approaches (e.g. general additive models, logistic regression) only marginally increased overall map accuracy over discriminant analysis. Last, the probabilistic-deterministic LANDSUM landscape fire succession simulation model (Keane *et al.* 1997*a*, 2002*b*) was used to generate fire regimes for the lower Selway landscape to demonstrate a simulation approach. Fire frequency estimates were averaged across all pixels over all years in a 1000-year run and fire severity was computed from the modal value simulated for each pixel.

Simulation sensitivity analysis

In the Keane *et al.* (2003) study, it became apparent that simulation modelling was one of the best strategies for generating fire regime maps. Yet, they found many limitations to this complex and demanding strategy. To address these limitations, we conducted three simulation experiments to assess the importance of various modelling parameters for generating fire regime maps using the same Lower Selway watershed. First, we multiplied the input point-based fire frequency probabilities (inverse of fire return interval) in the LANDSUM model by 0.5, 1.5, 2.0, and 2.5 to assess the sensitivity of fire ignition parameters in generating accurate fire regimes. Next, to illustrate the importance of temporal scale in fire regime descriptions, we created fire regime maps from 100, 250, 500, 1000, and 1500-year simulation runs. We attempted to include a 10 000-year simulation in this exercise but lacked sufficient computing resources and time. The average fire size parameter in LANDSUM (see Keane *et al.* 1997*b*, 2002*b* for details) was then assigned five values (50, 100, 500, 1000, and 5000 ha) to ascertain the importance of the fire size distribution function on landscape fire regimes (the observed value for the study area was 50 ha). For the two fire parameter simulation experiments, we averaged and computed modal values of fire occurrence and severity respectively over 500-year simulation runs. We used the observed fire parameter values for the simulation time span experiments (1.0 fire size multiplier and 50 ha fire size parameters). Even though LANDSUM has stochastic elements, we performed only one run for each simulation experiment because previous analyses showed inherent fire ignition stochasticity had a minor effect on landscape-level LANDSUM results (Keane *et al.* 2002*b*). And, we only report fire frequency characteristics in the form of landscape fire return interval (average fire return interval for all pixels on the landscape) for simplicity and brevity.

Simulation model comparison

Differences in simulation models also have a great effect on resultant fire regime prediction. Each simulation model is developed with specific purposes, ecosystems, and landscapes in mind, and this limits the application of models to other areas, ecosystems, or situations (Gardner *et al.* 1999). We compared the complex mechanistic model FIRESCAPE (Cary and Banks 1999; Cary 2002) to the simple pathway model LANDSUM (Keane *et al.* 2002*b*) to explore the importance of topography, fuels pattern, and climate in fire regime generation across models. We applied these models to neutral landscapes of 1000×1000 pixels of 50 m width where topography, fuels, and climate were varied in a factorial design. Simulation parameters (i.e. succession, climate, fire frequency, and fire size) for each model were taken from the native landscapes for which the model was built to eliminate geographical bias in model development.

Topography was modelled as flat, moderate, and mountainous using a 2-dimensional sine function with a periodicity of 16.7 km or 333 pixels (i.e. elevation relief for flat was zero, moderate was 1250 m and mountainous was 2500 m) (Fig. 1*a*). Spatial fuel distributions were created using three patterns: homogeneous, random, and clumped (Fig. 1*b*, *c*). Ten replicates of the clumped fuel pattern were generated using an unpublished algorithm (personal communication, R.H. Gardner). It involved invoking randomly orientated and located elliptical disturbance patterns of varying size to set back the 'age' of fuel or community by 0.1 from a maximum of 1 indicating the highest fuel loadings. The 90th percentile size of the ellipses was 100 ha and the aspect ratio of the axes was set at 0.8. The set back of 'age' in overlapping ellipses was additive and new ellipses were added until a landscape average 'age' setback of 0.25 was achieved. For FIRESCAPE, these setback age values were translated into fuel amounts via a negative exponential fuel accumulation curve (Olson 1963) using a steady-state litter load of 1.637 kg m^{-2}, which is the average steady-state fine litter loading observed for high elevation (>1500 m) sites in the Australian Capital Territory (ACT) region, and a decomposition constant of 0.3 (Cary 1998). For LANDSUM, fuel 'age' was classified into eight classes of sequential stages of vegetation succession where the youngest fuel (<0.12) and the

(*a*) (*b*) (*c*)

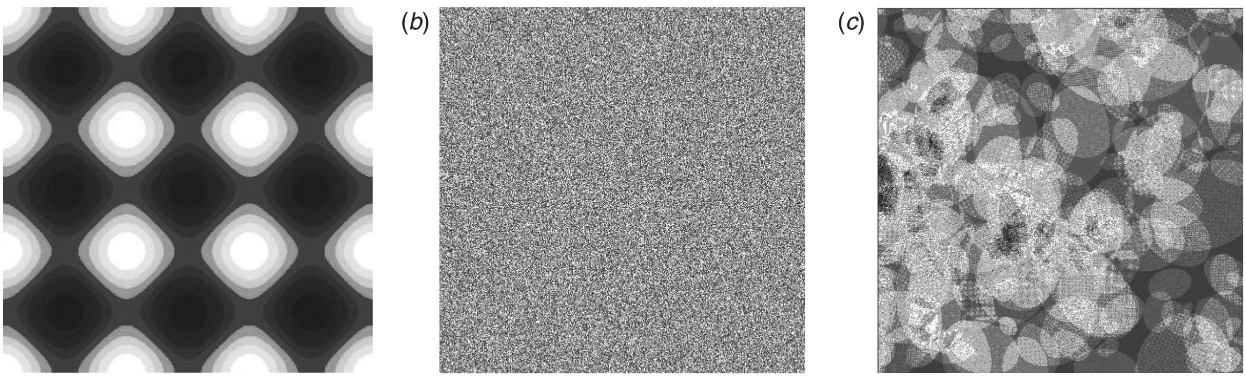

Fig. 1. Fuels input layers used in the comparison of FIRESCAPE (Cary and Banks 1999) and LANDSUM (Keane *et al.* 2002*b*) for predicting fire regimes. (*a*) Elevation (dark areas are low); (*b*) random fuel assignment; (*c*) clustered using ellipses of varying size. The homogeneous fuel layer is not shown because it would be a square of one color (i.e. one fuel type).

climax community allocated to the oldest fuel (>0.88). In this fashion, the 10 replicates of clumped fuel 'age' were transformed into input data appropriate for each model.

For the observed weather, 10 yearlong sequences of daily weather were chosen from 42 years of daily records at Glacier National Park, USA (LANDSUM) and 42 years of simulated weather from a weather generation algorithm (Richardson 1981) implemented for the Australian Capital Territory Region (FIRESCAPE). The generation algorithm produces sequences of weather with similar statistical qualities as that of observed data from the region (Cary and Gallant 1997) and is the primary weather component of the FIRESCAPE model. Weather years were chosen so that they best matched the variation in average daily maximum temperature (°C) and average daily precipitation (mm) across all years available at each location. These weather streams defined a Current scenario that was then modified to create two additional climate change weather scenarios by adding 3.6°C to daily temperatures (Cubasch *et al.* 2001) and multiplying daily rainfall by 0.8 and 1.2 to create the warm, dry scenario and warm, moist scenario, respectively.

A total of 2700 1-year-long simulations without succession were run for each model given 27 unique combinations of elevation (mountainous, moderate, flat), fuel pattern (clumped, random, homogeneous), and climate (observed, warm-dry, warm-moist) and 10 replicate maps of each fuel pattern and 10 replicate sequences for each weather scenario. Since LANDSUM has several stochastic functions, each simulation was repeated 10 times. The number of fire ignitions and the total area burnt per year were recorded for each 1-year simulation. Fire ignitions were defined as ignitions that successfully spread to at least one pixel adjacent to that where the fire was initially ignited. The area burned and number of ignitions was written to computer files that were later analysed using a fully factorial ANOVA design with the SAS statistical package (SAS Institute 1990). This model comparison method was the prototype for a more robust model comparison using several other spatially explicit landscape fire succession models by the authors.

Results and discussion

Mapping strategy comparison

Fire regime maps created from the three strategies were quite different in both frequency and severity for a variety of reasons (Fig. 2*a*–*c*). Rule sets and parameters used in the classification strategies are syntheses of empirical data, expert knowledge, and observed experience for the study area (Barrett and Arno 1992). As such, these rules represent a coarser spatial, temporal, and category resolution than that of statistical and simulation strategy and this resolution is manifest in the maps because Barrett and Arno (1992) believed a large portion of the landscape was in frequent, mixed severity fire regimes (Tables 1 and 2). Neither the classification nor statistical strategy incorporated spatial relationships into predictive models; that is, adjacent stands or surrounding topography did not influence fire dynamics. Statistical strategies ultimately rely on comprehensive and accurate field data, and the field data from this study were reasonably representative of the biophysical environment, but were limited by sample size (only 64 plots) and temporal depth (approximately 200–300 years of fire history). As a result, very little of the landscape was mapped to frequent, non-lethal surface fire regimes because there were few plots that represented this regime (Tables 1 and 2). Simulation modelling provided greater temporal depth (1000 years) but results were further removed from reality because they incorrectly assume that the model accurately simulated fire ignition, growth, and intensity. Most of the landscape is in the moderate fire return interval class because fire frequencies were averaged over only 1000 years, and most fires were long fire return interval and stand replacement, so many pixels did not have a rich history of all three severity types (Keane *et al.* 2003).

Statistical strategies are the most accurate because they best represent the data used to construct and validate the models (Tables 1 and 2). But, the Kappa statistic is low because of the uneven distribution of field plots across frequency and severity types due to the absence of fire history records on the study landscape for long fire return interval ecosystems. A surprising result is the value of physically based variables in statistical analysis. Ecosystem process variables, summarized from Biome-BGC simulations, not only increased accuracies by 10% for both maps, they also tended to portray spatial relationships at the scale of fire regime dynamics better than other indirect variables. This is because the Biome-BGC model integrated coarse scale weather (2 km resolution) with mid-scale soils data (100–500 m resolution) and fine scale vegetation (30 m resolution) to quantify ecosystem process such as net primary productivity, heterotrophic respiration, and evapotranspiration, that directly influence fire and fuel dynamics, at the appropriate predictive scale (Keane *et al.* 2002*a*). Statistical analysis with only topographical variables tended to exploit inconsistencies in the DEM (Digital Elevation Model) because there is only one scale represented—30 m (Keane *et al.* 2003).

Both classification and statistical strategies are used extensively because they are somewhat simple, data-driven, and easy to implement (Morgan *et al.* 2001; Keane *et al.* 2003). Using classification strategies, land managers can quickly and easily create predictive fire regime maps with little field data using expert opinion, but these maps often lack a measure of error or statistical variability so they may contain considerable errors. Fire regime maps created by statistical strategies provide these measures but they are limited by the scope of the data (e.g. geographic region, temporal depth, ecosystem, and biophysical setting) and it is important that the independent or predictor variables be mapped across the entire analysis landscape, which is rarely the case for many

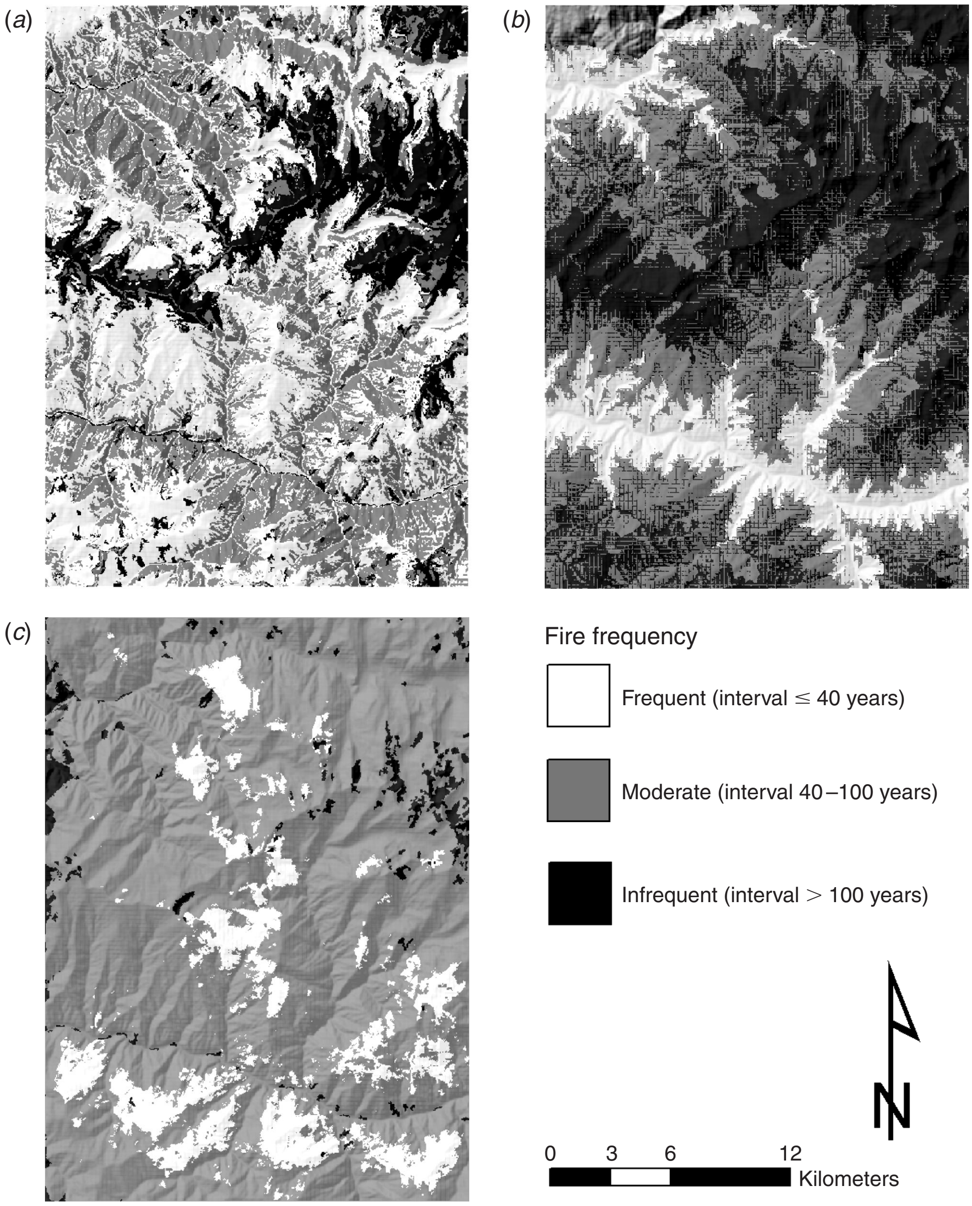

Fig. 2. Resultant fire regime maps of fire frequency created using the three strategies of classification, statistical analysis, and simulation modelling. (*a*) Fire frequency using classification strategy (Barrett and Arno 1992); (*b*) fire frequency using statistical analysis strategy (discriminant analysis); (*c*) fire frequency using simulation modelling (LANDSUM).

lands. The complexity of classification and statistical strategies is much less than a simulation strategy where extensive expertise in computer programming, landscape ecology, fire dynamics, and mapping is needed to create landscape fire succession models. Moreover, simulation models are notoriously difficult to parameterize, initialize, and execute.

Nevertheless, we found simulation modelling superior to classification and statistical strategies for mapping fire regimes with respect to several desirable aspects. First, the temporal depth of fire history field data needed to develop extensive and comprehensive rule-based or statistical models is often limited. Fire history studies in many forested ecosystems have only a 200–500-year fire record taken from a spatially and temporally discontinuous record (i.e. fire scars). Many fire dominated ecosystems of the world, such as in Australia and central Africa, lack extensive fire scar records because there are few plants that record a fire scar and a discrete annual growth ring record. Simulation models can be executed for long periods so resultant fire regimes are summarized across ecosystem-appropriate time spans. Many simulation models integrate important landscape processes, such as fire, weather, and succession, across multiple scales

Table 1. A comparison of the *fire interval classes* generated from the three fire regime mapping strategies

Numbers inside the table represent the percentage of the Lower Selway landscape that was predicted for each fire return interval class. The last row shows the percentage of plots in each fire return interval category ($n = 64$)

Strategy	Fire return interval			Map agreement with plot data	
	Frequent (<40 years)	Moderate (40–100 years)	Infrequent (>100 years)	Overall % correct	Kappa statistic
Classification	46.2	36.7	13.4	33.00	0.15
Statistical	17.8	41.5	40.7	64.58	0.40
Simulation	14.4	82.3	3.3	31.25	0.00
Percentage of field plots	12.5	50.0	37.5	100.0	

Table 2. A comparison of the *fire severity classes* generated from the three fire regime mapping strategies

Numbers inside the table represent the percentage of the Lower Selway landscape that was predicted for each fire severity class. The last row shows the percentage of plots in each fire severity category ($n = 64$)

Strategy	Fire severity class			Map agreement with plot data	
	Non-lethal surface fire (% landscape)	Mixed severity fire (% landscape)	Stand-replacing fire (% landscape)	Overall % correct	Kappa statistic
Classification	14.9	66.3	15.1	50.0	0.19
Statistical	5.7	52.3	41.9	72.9	0.51
Simulation	7.1	22.4	70.5	39.6	0.00
Percentage of field plots	8.3	56.3	35.4	100.0	

into one comprehensive application. Landscape fire succession models also have the ability of integrating spatially discontinuous point data for fire history, biophysical settings, and vegetation composition (used to quantify input parameters) into one cohesive spatial application. Simulation models can be modified to include explicit representations of the factors that influence fire regimes, such as climate and humans. For example, Cary and Banks (1999) simulated fire regimes under different climate scenarios for a landscape in the Brindabella Range, ACT (Cary 2002), and Wimberly *et al.* (2000) simulated fire regimes under current fire exclusion policies for a large landscape in western Oregon, USA. And last, simulation models that predict fire regimes can be used for many other purposes, such as predicting wildlife habitat, watershed erosion, and fuel loadings for various management alternatives.

Simulation sensitivity analysis

As expected, the simulation parameters greatly influenced simulated spatial fire regimes (Fig. 3; for brevity only fire frequency is shown). Landscape fire return intervals increased 8–15% when site-level fire ignition probabilities were multiplied by 0.5, and return intervals decreased 8–15% when probabilities were multiplied by 1.5. However, when these probabilities were multiplied by 2.0 and greater, it appears the landscape fire return interval stabilized at ~25% below that observed for the landscape. This indicates that the pattern of recently burned communities and the landscape size greatly influence fire return interval as fire ignition frequencies increase. The same phenomenon is found in the fire size parameter experiment (Fig. 3*c*). Landscape fire return intervals tend to stabilize around 28 years as the average fire size parameter increases compared to the 60–80 years observed for the Lower Selway landscape. Again, the small landscape extent (51 000 ha) and the increased presence of seral communities that have low ignition probabilities heavily influence landscape fire regime characteristics. Between the two fire parameters, average fire size appears to have the greatest effect on simulated fire regimes and, therefore, should be estimated with greater accuracy (Fig. 4). An error of 20% in estimating fire probabilities might only result in a 5–10% error in landscape fire return interval, but the same error in average fire size estimation might result in an error of greater than 50% in landscape fire return interval (see the example in Fig. 4).

Simulation length is very important in the computation of landscape fire return interval (Fig. 3*b*). Short simulation periods (<300 years) were not long enough to adequately represent fire frequency and severity, especially in long fire return interval ecosystems such as subalpine forests. The fire return interval started to converge to observed values after ~300 years of simulation indicating that at least 500 years and preferably 1000 years should be used to compute fire severity

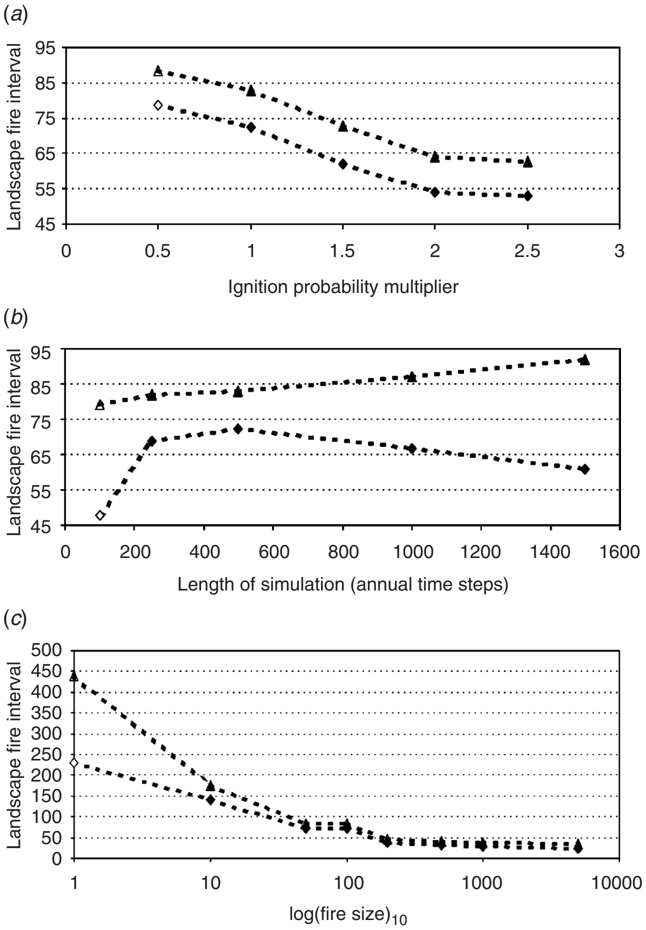

Fig. 3. Response of landscape fire interval to simulation parameters in LANDSUM. (*a*) Ignition probability multiplier (using 500 year simulation period, 50 ha fire size parameter); (*b*) length of simulation (1.0 ignition probability multiplier, 50 ha fire size parameter); and (*c*) fire size parameter (500 year simulation, 1.0 ignition probability multiplier). Triangle data points show landscape fire interval calculated by including areas that do not burn (i.e. rock/barren); diamond data points show landscape fire interval calculated without these unburnable areas.

and frequency maps for the Lower Selway landscape. Cary (1998) found a similar result for inter-fire interval, intensity and season of occurrence in the Brindabella Range study. The diversity of fire history increases as simulation length becomes longer, resulting in a greater resolution in fire return interval calculations (Fig. 5). It appears that the first 200–400 years should not be included in the computation (Fig. 3*b*). The simulation time span and the initial span of years to exclude from the analysis is landscape specific, depending on topography, fire return intervals, and climate, so it is probably best to run the model long enough so there are at least 5 fires per map unit (i.e. pixel or polygon). In short interval fire systems, such as the tropical savannas of Australia, this time would be significantly shorter, especially when burn sizes are often larger than those of the USA Rocky Mountains.

An unexpected result is the importance of unburnable landscape elements (e.g. rock, water, snowfields) to the computation of landscape fire regime characteristics (triangle *v.* diamond data points in Fig. 3). The average landscape fire return interval increased ∼15% when these areas were included in the calculation for this study area, regardless of input fire frequency or fire size parameterization (Fig. 3*a*, *c*). Landscape fire return interval monotonically increased as simulation length increased because the fire return interval for these areas is assigned the simulation time length in our algorithm (Fig. 3*b*). This is illustrated in Fig. 5 by the number of pixels with a return interval equal to simulation length (bar furthest right on histograms). When these areas are excluded, the landscape fire return interval eventually will converge to a somewhat stable value; it did not in our experiment because we were unable to generate a simulation length long enough for the study area due to computational limitations.

Simulation model comparison

There were major differences between the two landscape fire succession models FIRESCAPE and LANDSUM (Fig. 6). The three factors of terrain, fuels, and climate explained only 25% of variation for LANDSUM simulations but over 60% for FIRESCAPE simulations. This indicates that FIRESCAPE has a more complete integration of the processes influencing fire regimes, mainly climate and topography. FIRESCAPE contains a climate driver linked to fire ignitions coupled with a comprehensive fire spread model. However, LANDSUM appears to have a greater sensitivity to the patterns of fuels on the landscape, probably because the model simulates a greater differentiation in fuels (Fig. 6).

These results are entirely explained by the inherent design of each simulation model. LANDSUM was developed to simulate fire, vegetation, and landscape dynamics with a minimal set of simple input parameters (Keane *et al.* 1996*a*, 1997*b*, 2002*b*). As a result, LANDSUM does not include daily weather, direct estimations of fuel load, and a highly mechanistic fire spread model, thereby explaining its low sensitivity (low r^2) to climate and topography factors (Fig. 6). FIRESCAPE contains a daily climate driver, a direct simulation of fuel loads, and a comprehensive fire spread component (Cary and Banks 1999; McCarthy and Cary 2002). LANDSUM was built for those landscapes where fire history evidence can be collected and summarized into appropriate model parameters (e.g. fire frequencies from fire scars). The ecosystems that FIRESCAPE was developed for rarely contain fire history evidence so a more complex integration of fire processes with climate was warranted (Cary and Banks 1999).

Four factors ultimately dictate landscape fire succession model design: (1) diversity of ecosystem processes affecting fire regimes; (2) availability of field data; (3) planned application; and (4) computing resources. LANDSUM was developed for northern Rocky Mountain ecosystems in the

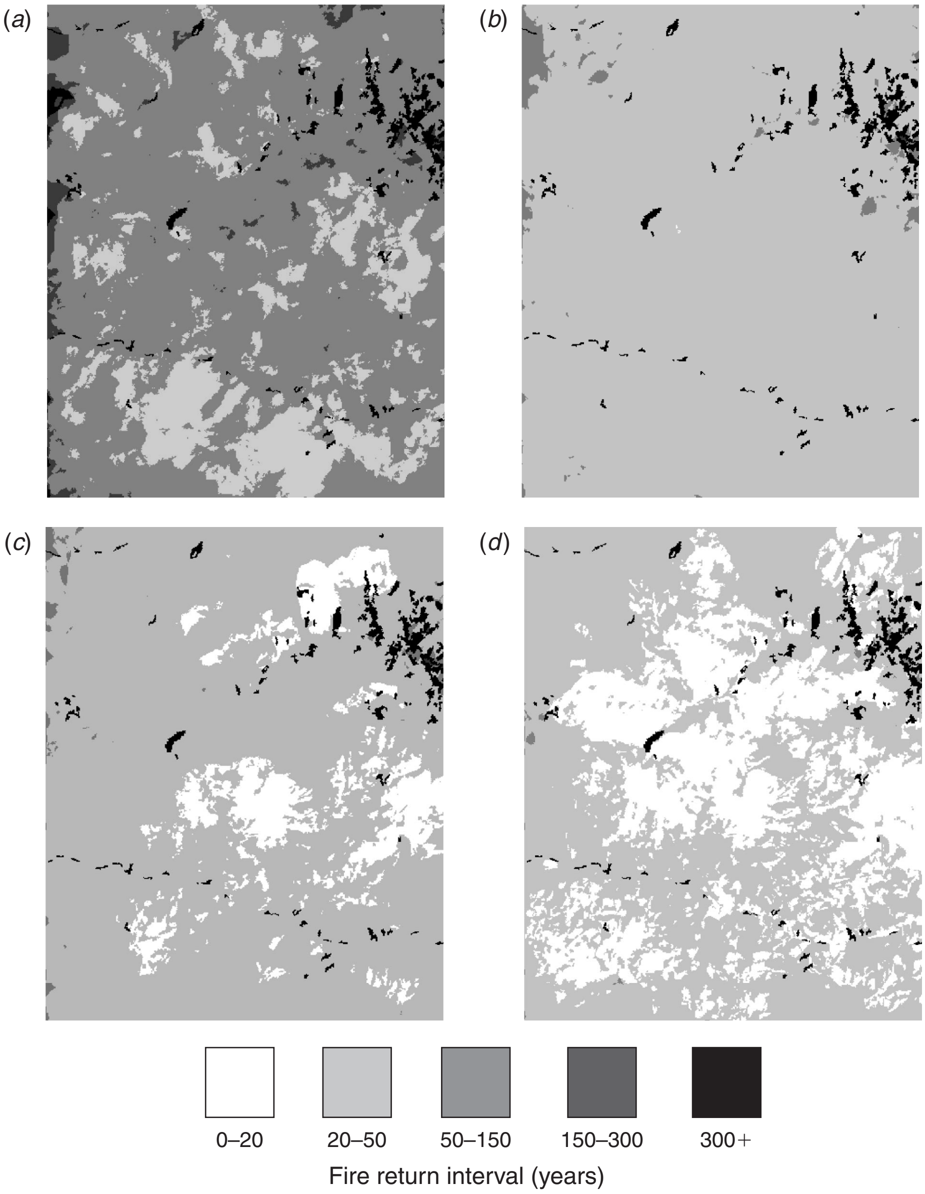

Fig. 4. Fire frequency maps created over 500 year simulations using the observed fire ignition probabilities but changing the fire size parameter. The same random number sequence was used for each simulation to eliminate stochastic variability between runs. Fire size parameters used in these simulations were (*a*) 100 ha, (*b*) 500 ha, (*c*) 1000 ha, and (*d*) 5000 ha.

western United States while FIRESCAPE was developed for eucalypt forests of south-eastern Australia. Differences in fire regime characteristics within these two areas, along with the available field data and planned application, dictated model design and development. The selection of the most appropriate model for application to other landscapes requires the user to evaluate several factors. First, the output must be pertinent to the user's application. Second, the data to parameterize and initialize the model must be available and of sufficient quality and quantity. Next, the model must contain an explicit simulation of the processes that control fire regimes for the landscape in question. Last, there must be sufficient computing resources and expertise available to execute the model and interpret its results.

Challenges and opportunities

There are six primary challenges in predicting fire regimes across a landscape. The first is matching or rectifying the spatial and temporal scales that govern fire and landscape dynamics (Simard 1991). Fire is a complex disturbance process manifest at many time and space scales, yet many fire regime studies describe fire dynamics at the stand-level

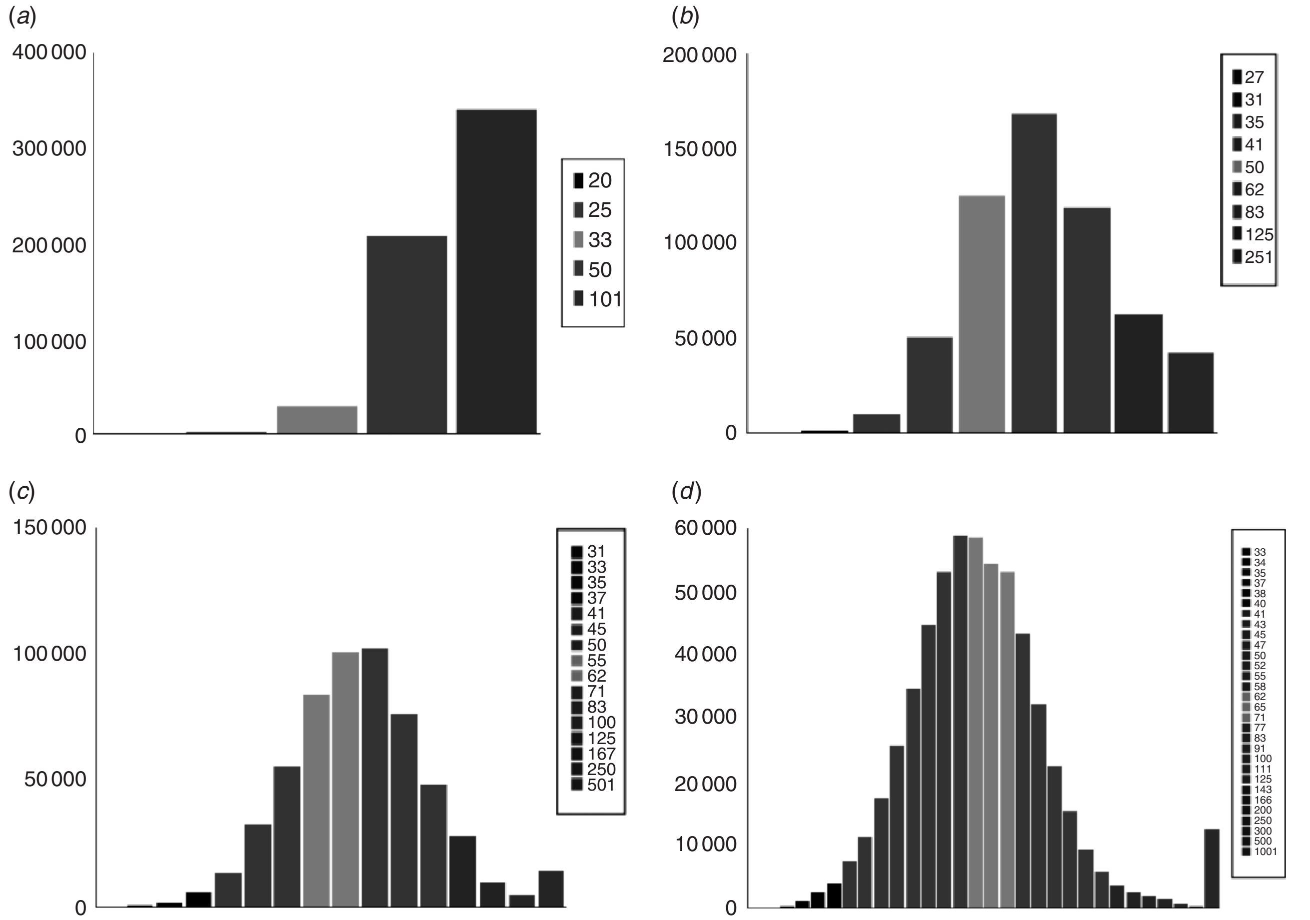

Fig. 5. Changes in resolution in the computation of fire intervals with increasing simulation length. Shown is the frequency distribution of pixels by fire return interval (years) for the following simulation lengths: (*a*) 100 years (5 distinct interval values); (*b*) 250 years (9 distinct interval values); (*c*) 500 years (16 distinct interval values); and (*d*) 1000 years (32 distinct interval values).

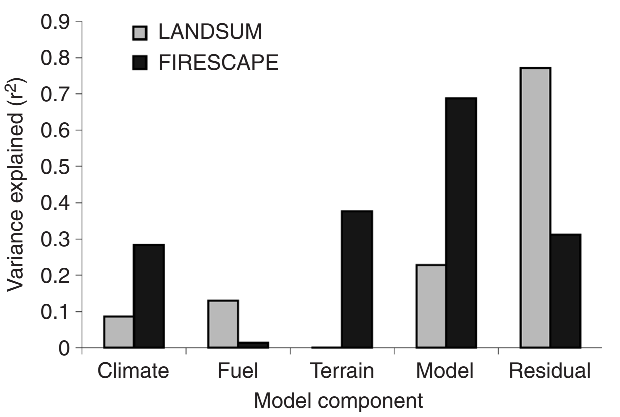

Fig. 6. A comparison of the FIRESCAPE and LANDSUM landscape fire succession models using an ANOVA analysis on factorial simulation experimental design of climate, fuels, and terrain for simulated output of burned area and number of fires. Shown is the amount of variance explained by each factor and their interactions using the correlation coefficient or r^2. Residual is the variation in model output not explained by the three factors.

across relatively short time spans. For example, lightning dynamics is an important and complex process that is rarely integrated into predictive fire regime models because of its large scale requirements (Knight 1987; Agee 1991), although Cary (1998) includes a lightning location model in the Brindabella Range Study.

The second challenge is including all the elements that characterize fire regimes (frequency, severity, pattern, fuel type, seasonality) into a comprehensive predictive model. Frequency can be easily quantified from point- or stand-level data, and fire pattern (i.e. size and shape of burned patches) is evaluated from fire atlases or simulated from models; however, fire seasonality requires long-term climate records and an assessment of the phenological stages of affected vegetation. Fire severity not only depends on stand-level fuel characteristics (Ryan and Noste 1985), but also the location of that stand in the landscape matrix (Camp *et al.* 1997) and the dynamics of coarse-scale wind patterns for that stand (Swanson *et al.* 1997).

The third challenge is accounting for the inherent spatial, temporal, and process (severity or intensity) variability within a fire regime, which is ultimately responsible for landscape structure and composition (Heinselman 1981; Agee 1993; Gill and McCarthy 1998; McKenzie 1998). For example, the variability in fire return interval is essential for assessing the degree of departure from historical conditions along with designing fire treatments, assessments and schedules for landscape management (Landres *et al.* 1999). Fire pattern variability dictates the size and shape of future treatments that attempt to emulate natural fire (Hunter 1993). And, the range of fire severities experienced within a fire regime will guide treatment design and implementation (Keane 2000). Yet, most fire regime models rarely characterize the inherent variability of the predicted variables of fire frequency or severity.

The fourth challenge is avoiding the possibility that developed fire regime prediction models will become obsolete once predicted climate change, exotic invasions, and changes in land management become reality (Shinn 1980; Weber and Flannigan 1997). Future changes in climate will render most maps inaccurate unless the models used to describe fire regime contain a link to climatic processes or other change agents.

The fifth challenge is designing useful fire regime classification categories for use across diverse local, regional, and national applications. The range of fire return intervals that define a frequency category may not be optimal across all landscapes in a region or across all space scales. For example, Hardy *et al.* (2001) defined their frequent fire category as lands having mean fire return intervals between 0 and 35 years, yet 35 years might be especially long for some grasslands and very short for some forests. Such a broad range may not provide sufficient distinction between important fire regimes on dry, fire-prone landscapes. And, the interpretation of this somewhat arbitrary range might be misleading for many management applications; managers might use the mid-point of this class as a target fire return interval without first evaluating evidence collected from their local landscapes and quantifying return interval and variability.

The last challenge is the collection and analysis of field data, which are critical for a myriad of fire regime prediction tasks because they provide the only truth for understanding, predicting, and interpreting fire dynamics (Morgan *et al.* 2001). Field data are needed to (1) design and describe fire regime characteristics and resultant classifications; (2) create predictive algorithms using statistical techniques; (3) parameterize and initialize simulation models; and (4) assess and validate predictive models and their results. However, many fire history sampling techniques have problems: (1) difficult to determine the spatial extent or pattern of fire events; (2) expensive to collect and analyse the data; (3) shallow temporal depth in some ecosystems; (4) insufficient records on the landscape; and (5) difficult to employ standard analytical and collection techniques because of ecosystem diversity.

Conclusions

The three major strategies for mapping fire regimes have unique advantages and limitations that dictate their application:

- The classification strategy is relatively quick, easy, and simple and works best when there is very little fire history data. However, it does not account for spatial relationships and tends to be inaccurate and portray fire regimes at a coarse scale.
- The statistical strategy is also relatively easy, straightforward, and popular, and it is the most accurate, but this data-driven approach requires copious field data that are expensive and difficult to collect, and this strategy requires extensive expertise in statistical modelling.
- Simulation models are complex computer programs that are often difficult to parameterize, initialize, and execute. However, the simulated fire regimes have the deepest temporal depth; integrate complex multiscale spatial interactions; and can be used to explore alternative fire regimes under changing climate and vegetation.

The simulation strategy appears to generate the most robust and realistic fire regimes because of the deep temporal record, but quantification of several parameters is very important in the simulation:

- Estimation errors for fire ignition probability parameters may result in minor differences in simulation results, whereas minor errors in the average fire size parameter could have major influences on subsequent fire regime simulations and mapping.
- The simulation time span should be long enough for the majority of the map units (pixels or polygons) to experience at least 3–5 fires.
- Results from these simulation experiments are landscape specific and may be significantly different for other landscapes, ecosystems, or models.

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